Proceedings of CONF-CDS 2025 Symposium: Application of Machine Learning in Engineering
DOI: 10.54254/2755-2721/2025.AST36125

Decision Tree-Dominated Robotic Intelligent Systems: A Review of Feature Dimensionality Reduction and Explainable Architectures in Perception and Navigation

Jiahui Liu

Measurement and Control Technology and Instruments, Shenzhen University, Shenzhen, China
helen_liu1014@163. com

Abstract. With advances in autonomous navigation, decision-tree based intelligent systems have gained popularity because of their well-defined structure and clearly interpretable reasoning process. We investigate here the recent progress in key challenges faced by the decision-tree model for robotic perception and decision making such as handling high-dimensional sensor data online, being expressive enough in complex nonlinear environments, etc. Trade-offs are found between the interpretability of various learned models and their performance. Furthermore, how robust they are when put into practice. And apart from tackling these challenges, in this section we outline future directions on research, such as: integrating decision trees and deep neural networks or graph-based models; proposing adaptive FCMs to speed up sample traversal; developing hierarchical interpretability; constructing neuro-symbolic hybrid systems; and building self-evolving DMs for open-world navigation.

Keywords: Decision Trees, Robot Navigation, Robot Navigation

1. Introduction

1.1. Research background and motivation

In recent years, intelligent robotic systems have been widely applied in various fields such as industrial manufacturing, smart transportation, service robots, and disaster relief. With continuous advancements in computing power and sensing hardware, robots are evolving from traditional rule-driven systems to autonomous intelligent systems capable of self-perception, reasoning, and decision-making. Among these, environmental perception and path navigation enable robots to reach their autonomous goals regardless of obstacles in an unknown environment, directly affecting how successfully they perform in these conditions [1]. For robots to understand their complex environments, many advanced robots use various sensor types (LIDAR, RGBD camera, IMU, etc.) , with machine learning algorithms that model, analyze and make decisions from perceptual data provided by the sensors. Because these processes generate high dimensional multimodal datasets, these models must be more sophisticated than those used previously and as such impose greater

DOI: 10.54254/2755-2721/2025.AST36125

requirements on real-time systems, while putting a strain on the robustness and interpretability of perception systems as well.

1.2. Research status and problem orientation

While "black-box" models like deep learning have achieved remarkable success in subtasks such as robotic vision, semantic mapping, and path planning, they generally face two critical challenges [2]. First, the computational and generalization bottlenecks caused by high-dimensional perception data —particularly in resource-constrained platforms (e.g., mobile robots and autonomous vehicles) — where model complexity severely hampers deployment efficiency [3]. Second, lack of interpretability means the decision-making process remains hidden from human users and makes it difficult to do debugging and diagnostics as well as verify the safety. For safety-critical systems like autonomous driving, there is a great urgency for introducing algorithmic frameworks that have structured reasoning ability, strong control capability, and clear interpretability. In order to facilitate higher level decisions using perception data for autonomous systems, transparent reduction of data dimensionality as well as accurate yet interpretable decision paths at various levels is becoming one of the important research areas for intelligent robotic systems.

As a traditional machine learning approach based on rule induction and recursive partitioning, decision trees and their ensemble variants (such as random forests and gradient boosting trees) demonstrate unique advantages in robotic systems. First, decision trees inherently support heterogeneous feature processing, enabling simultaneous handling of continuous, discrete, and structured inputs. Second, their tree structure provides excellent interpret ability, with each split corresponding to a specific feature threshold judgment that facilitates human understanding of model behavior [4]. Third, decision trees incorporate an importance evaluation mechanism during feature selection, automatically compressing and filtering feature dimensions during training to effectively reduce computational load. Additionally, compared to complex models like deep neural networks, decision trees are advantageous for small sample learning and incremental training due to their generality and convenient engineering implementation compared with feed-forward deep nets. In this case, decision trees are taken into account in exploration of robotic intelligent systems based on decision trees in perceptual tasks and navigation under 3D LiDAR sensing, primarily discussing recent advancements and emerging opportunities regarding high-dimensional feature representation and model interpret ability formulation [5].

2. System architectures and applications

2.1. An application example of decision tree in mobile robot navigation system

In mobile robot navigation tasks, decision tree models are widely used in critical modules such as path selection, obstacle avoidance, and behavior planning. Compared to deep learning methods, decision trees demonstrate greater robustness with smaller datasets and are easier to debug and maintain in practical applications. For instance, in indoor service robot systems based on visual navigation, researchers employ CART (Classification and Regression Tree) models to classify image features captured by cameras to determine whether obstacles exist or accessible areas are available. Additionally, embedding random forests in SLAM (Simultaneous Localization and Mapping) systems can enhance the generation of map semantic labels, enabling more semantically-aware path planning as shown in Figure 1.

DOI: 10.54254/2755-2721/2025.AST36125

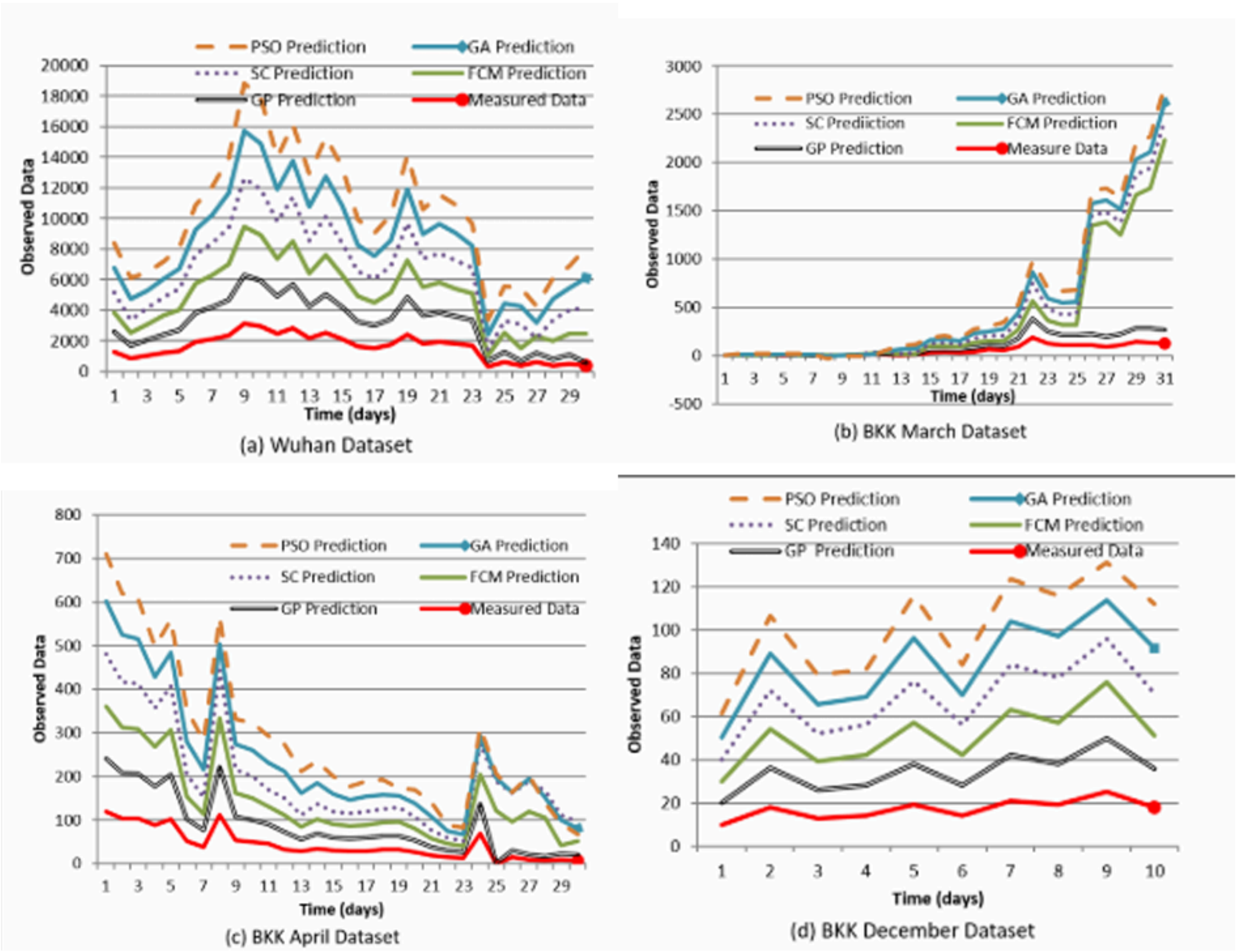

Figure 1. Construction and geometrical dimensions of specimens

Stem from [6]: Abdullahi S B, Muangchoo K, Abubakar A B, et al. Data-Driven AI-Based Parameters Tuning Using Grid Partition Algorithm for Predicting Climatic Effect on Epidemic Diseases [J]. IEEE Access, 2021, 9: 55388–55412.

Many real-world applications have adopted the "perception-decision-execution" loop by blending decision trees and heuristic search schemes such as the A* algorithm for actual tasks; for instance, robots can employ decision trees to determine whether an identified environment (say if a walkway is obstructed) in the form of a plan and switch between plans accordingly, reducing computational cost and improving both real-time responses and reactivity by leveraging both techniques.

2.2. Feature compression and decision path optimization in the perception system of autonomous vehicles

In autonomous driving systems, vehicles must process high-dimensional inputs from multi-source perception modules including LiDAR, cameras, radar, and GPS. Given the massive data volume generated by these sensors, the system must complete recognition and decision-making within milliseconds, which imposes extremely high demands on feature processing and model efficiency. In recent years, researchers have introduced decision trees and their enhanced variants into perception systems to achieve effective feature dimension compression and real-time path optimization [7].

DOI: 10.54254/2755-2721/2025.AST36125

For instance, in subtasks such as traffic sign recognition, vehicle detection, and pedestrian identification, Gradient Boosted Decision Trees (GBDT) are employed to train compact yet efficient classifiers. This approach not only enhances inference speed but also maintains high-precision recognition performance. By integrating a feature importance evaluation mechanism, the system dynamically eliminates low-contributing features while retaining only critical dimensions for navigation decisions, thereby reducing computational resource demands. Furthermore, advanced autonomous driving systems (e.g., L3-L4) integrate decision trees with rule engines to establish auditable decision path graphs, meeting regulatory requirements for system explainability and safety reviews.

2.3. Fusion and processing mechanism of multi-modal sensor input

Modern robotic systems make use of various kinds of sensors like vision, laser, voice, tactile sensations to know their surrounding environment better and can respond to it. But there is still an issue as how to integrate the signals of different modalities effectively and homogenously into a single robot brain signal in order to implement suitable action plans for the robots. Decision tree approaches are one of the frequently used methods because decision tree processes are good at handling heterogeneous data, especially for construction of unified classification or regression model with multi-modal inputs.

For instance, in post-disaster search-and-rescue robot systems, image data is used to identify passage routes, infrared sensors detect temperature anomalies, and acoustic sensors determine potential survivors. By feeding multimodal features into random forest or extreme gradient boosting tree (XGBoost) models, we can achieve collaborative analysis of different signal sources and adaptive weight allocation, thereby enhancing overall decision accuracy. Compared with deep fusion-based neural network models, decision tree approaches not only have lower input format requirements but also offer easier model updates and explanations, effectively improving system engineering maintainability.

2.4. Robustness in dynamic environment and path replanning strategy

In densely populated areas or chaotic traffic situations, robots should respond to incidents like changes in the environment or signals appearing and disappearing, which happens all of a sudden, in a real-time fashion; in contrast, conventional path planning models used traditional pre-defined static maps and prescribed rigid rules, which did not offer any degree of adaptation to sudden changes in situations. To solve the above problems, a number of researchers utilized decision trees in dynamic state perception and path re-planning modules so that these models of machine can deal more robustly and promptly with uncertain information during trajectory tracking.

A common way is to build a "state-action" decision tree model. Once the robot finds that the environment has changed, it will re-assess the feasibility of the target path immediately and find some alternate behavior path from the tree structure (detour/wait/speed change), and some reinforcement-enhanced methods also take the real-time perception data into the gradient boosting tree model to predict the path interruption risks and give commands to preemptively avoid them. Compared with the RL-based methods, this strategy shows higher transparency and controllable reaction speed, which makes this method very suitable to be used on safety-critical systems where redundancy is required such as medical robots or smart wheelchairs.

DOI: 10.54254/2755-2721/2025.AST36125

3. Challenges and open issues

3.1. Real-time processing problem caused by high-dimensional perception data

Modern robots typically rely on multiple sensors (such as RGB images, depth maps, LiDAR, and inertial navigation systems) for environmental perception and state estimation. As sensing accuracy improves, the collected data exhibits high-dimensional and high-frequency characteristics, making real-time processing a system bottleneck. Although decision trees inherently possess certain feature selection capabilities and rapid reasoning properties, their performance remains constrained when handling high-dimensional, multimodal input data.

On one hand, excessive dimensions can lead to a significant increase in tree structure complexity during training, resulting in the "curse of dimensionality" that undermines model generalization. On the other hand, high-frequency inputs demand millisecond-level response speeds, posing severe challenges for embedded platforms with limited computing resources. Therefore, the critical challenge lies in effectively reducing input feature dimensions without compromising essential information while constructing lightweight and efficient tree structures.

3.2. The bottleneck of the expression ability of decision tree structure in complex nonlinear navigation environment

While decision trees can express logic and build the model in a very interpretable way, their capacity to model highly non-linear scenarios is relatively low. Navigation tasks require selecting trajectories, predicting obstacles, solving multi-objective problems etc. Under a single decision tree model, it tends to encounter overfitting problems or the problem that the decision tree partition granularity does not meet the demands of task. Moreover, traditional decision trees only adopt greedy local optimization. particularly evident in scenarios involving multiple interacting variables or nonlinear interactions. For instance, when dealing with unpredictable crowd movements or traffic rule changes, the tree structure may fail to produce stable and robust outputs. Therefore, there is an urgent need to explore effective integration of decision trees with deep learning models, graph neural networks, or fuzzy logic to enhance their expressive power and adaptability.

4. Conclusion

In the future, decision tree-based robotic intelligence systems will exhibit multidimensional evolution trends in perception and navigation. First, to enhance models' ability to represent complex nonlinear environments, deep learning methods like XGBoost and LightGBM will integrate with graph neural networks, creating hybrid agents that combine structured reasoning capabilities with interpret ability. Second, to address the high-dimensional challenge in dealing with multi-source sensing data, research is devoted to the establishment of the domain-adaptive feature-compression mechanism which uses attentional mechanisms to adaptively select the key inputs and uses transfer learning to improve generaliz ability for cross-task scenarios. Hierarchical explanation framework should be introduced in order to make decisions understandable from perception layer. Adding an additional dimension of the behavior and intent layers on top of high-security systems and a single unified metric-based evaluation for such systems. Decision trees are logical rule carriers used with deep models for complete closed-loop reasoning in cognizant robots in neural-symbolic fusion. This involves reasoning from perception to causality. To fit into open-world real-life environments with full uncertainty as well as changes of task-related needs and requirements, decision systems should

DOI: 10.54254/2755-2721/2025.AST36125

have lifelong learning ability and self-evolution capability so that they can keep their system robust and stable for long time without worrying about unexpected errors. Decision systems can do so by acquiring new information and structurally rearranging old information all the time. This research focus will contribute to the next-generation robotic perception and navigation system, being more intelligent, more adaptive, more learnable, and more explainable than before.

References

[1] Purcell, S. J., & Slepkov, D. A. (2025). Boosted decision trees for non-resonant background removal in hyperspectral CARS microscopy. *Journal of Physics: Photonics, 7*(3), 035024-035024.
[2] Chen, L. T., & Chang, C. P. (2025). Applying machine learning to analyze the key features of transit-oriented gentrification - A case study of Taipei metropolitan area. *Cities, 166*, 106195-106195.
[3] Barathula, S., Karthik, R., Alapati, K. J., et al. (2025). A multi-modal approach to pool boiling dynamics: Acoustic and vibration data for regime classification and heat flux prediction. *Thermal Science and Engineering Progress, 64*, 103760-103760.
[4] Sharma, S., Agyeman, T. B., Palimi, M., et al. (2025). Machine learning-driven pressure drop prediction in multiphase slurry hydrotransport. *Powder Technology, 465*, 121314-121314.
[5] Termeh, R. V. S., Niaraki, S. A., Shogrkhodaei, Z. S., et al. (2025). Human-based metaheuristics and non-parametric learning for groundwater-prone area mapping. *Ecological Informatics, 90*, 103326-103326.
[6] Abdullahi, S. B., Muangchoo, K., Abubakar, A. B., et al. (2021). Data-driven AI-based parameters tuning using grid partition algorithm for predicting climatic effect on epidemic diseases. *IEEE Access, 9*, 55388–55412.
[7] Lin, X., Wang, Z.-Q., Chen, X.-Y. (2020). Path planning with improved artificial potential field method based on decision tree. *2020 27th Saint Petersburg International Conference on Integrated Navigation Systems (ICINS)*.